Plant Disease Detection Using Deep Learning Algorithms: A Systematic Review

Muhammad Faizan Zeb[*], Ghassan Husnain[†], Waqas Ahmad[‡], Mohsin Tahir[§]

Abstract

Plant diseases may have a considerable influence on crop yield and food security. The impact of plant diseases on agricultural output and food security is debatable. Therefore, for effective treatment and prevention of many diseases, early detection and identification are crucial. Recently, deep learning algorithms have drawn increased interest as a means of developing automated plant disease detection systems. This article provides a review of neural network techniques for image data processing, With an emphasis on crop disease detection. It gives a general summary of the data collection methods, deep learning models and architectures, and different image processing methods applied to the analysis of imaging data. This survey aims to facilitate future research in enhancing the system performance and accuracy of deep learning-based plant disease detection, by exploring its potential capabilities.

Keywords: Plant disease, deep learning, neural network, CNN.

Introduction

Plant diseases are a major concern for farmers and the agricultural industry as a whole, as they can result in significant crop losses and decreased food production. The prompt and efficient identification of plant diseases is essential for successful disease management and prevention. Conventional techniques for detecting plant diseases, such as manual inspection by professionals, can be time-intensive and necessitate a significant level of expertise. Consequently, the rise of technology has spurred an increased interest in devising automated Infectious plant diseases that can be detected using machine learning and computer vision technologies. In addition, to improved speed and precision in disease diagnosis, these methods may lead to more effective disease management of plants and more timely treatment. It has been several years since systems have been developed that can diagnose different types of plant diseases, and the results have been encouraging. these technologies can revolutionize how we address plant disease management and ultimately

[*]Department of Computer Science, IQRA National University, Peshawar, 25100, Pakistan, faizanzeb.bcs@gmail.com

[†]Department of Computer Science, IQRA National University, Peshawar, 25100, Pakistan, ghassan.husnain@gmail.com

[‡]Department of Computer Science, IQRA National University, Peshawar, 25100, Pakistan, waqas.ahmad777@gmail.com

[§]Department of Electrical Engineering, IQRA National University, Peshawar,25100, Pakistan, mohsintahir85@gmail.com

play a vital role in ensuring food security for the increasing global population.

State of The Art Review

In computer vision, convolutional neural networks are being used to detect symptoms of plant diseases early (CNNs) according to the authors of a study (H. Tanrıkulu, M. H. Sazlı, 2022). To classify photos showing downy and powdery mildew on hops plants (Humulus lupulus). To increase the CNN model's effectiveness, we added fresh images that adhere to our standards and eliminated images that did not aid in learning. In a study(A. Elaraby, W. Hamdy,2022) the author focused on recognizing 25 different kinds of plant diseases across 5 different crops (Among the crops are wheat, cotton, grapes, corn, and cucumbers). To do this, we tapped into a publicly available picture collection that included both undamaged and damaged plant leaves that were taken in natural settings. Tested deep learning networks provide statistically significant results: Using AlexNet, a deep convolution neural network model, and particle swarm optimization, we achieved 98.83% accuracy, 98.56% specificity, 98.78% sensitivity, 98.67% precision, and 98.47% F-score.

In a study (M. Chohan, A. Khan,2020) the author’s in-depth study, How leaf photos can be used for automated segmentation and disease detection. To detect plant diseases using models, images are captured, preprocessed, segmented, augmented, features extracted, and classified. By utilizing various deep learning models Plant Village Dataset and the following neural network architectures are used to categorize five different plant diseases (Inception3 is a model based on VGG-16, ResNet-50, AlexNet, DenseNet-169, and DenseNet-169. Among all models tested, ResNet-50 had the highest accuracy rate of 97.80%. in comparing the models utilized for categorizing diseases.

A study presents an improved version of the suggested model that is faster and more accurate (A. M. Roy and J. Bhaduri,2021)as well as how it has been applied to identify a variety of illnesses that may affect apple trees. With 56.9 frames per second, the detection model improved from 91.2% accuracy to a 95.9% F1-score. Innovations in detection approach outperform current gold standard detection models. In complex, real-world orchard environments, the proposed model provides an accurate and reliable method to diagnose apple plant diseases.

In a study (2022) the author studies, A plan for classifying plant illnesses is proposed, with the use of the updated lightweight YOLOv5 model. By combining Ghostnet with WBF structure for lightweight feature fusion and BiFPN with rapid normalized fusion for weighted feature fusion, we might potentially increase the model's precision and effectiveness. With this method, each feature layer is trained independently, resulting in a model that emphasizes statistical measures more than other popular models. with an increase in operation time of 11.8% and an increase in accuracy of 3.98% and 92.65%, respectively. The plant disease categorization approach suggested in this work has been demonstrated to be effective, with a 92.57% accuracy rate on the custom-built dataset. Extending the model's usefulness in the future by making use of its ability to learn from other systems is a realistic possibility.

Figure 1: Flow Chart of Plant Disease Detection

In a study(Z. Chen *et al.*2022) the author studies, Using the foundation of the original YOLOv5 network structure, this research develops a better plant disease recognition and an accurate model for diagnosing plant diseases in extreme environments. The research presents two innovative approaches: An Involution Bottleneck module to minimize the number of inputs and computations while still collecting long-distance data in space, and a SE module to improve the model's sensitivity to channel properties. Rubber tree disease database images were used to evaluate the model, revealing an increase in accuracy of 5.4% over the baseline YOLOv5 network, with the mean average precision reaching 70%. For anthracnose and powdery mildew, 86.5% and 86.8% accuracy were achieved by the model, respectively. YOLOv5'ssignificantTotal detection performance was superior to its predecessor.

Throughout the paper(A. Ramcharan *et al,2018*) the author explains the study's purpose is to detect foliar disease symptoms in cassava (Manihot esculenta Crantz) by utilizing images and videos captured on a Tanzanian farm with smartphones. For this purpose, using convolutional neural networks, it is possible to identify objects in photographs and videos. Using 720 contaminated leaflets with varying degrees of infection (mild, moderate, and severe), the effectiveness of the model is assessed. The findings demonstrate that the F-1 score is lower for both severity levels when using images and videos captured A photograph of someone suffering from acute illness illustrates this fact more clearly, where the F-1 score dropped by 32% owing to a drop in model recall. The research concludes that, when designing CNNs for practical applications, it is crucial to optimize accuracy and recall performance to achieve the required performance in real-world conditions and to account for performance variations associated with different input data, such as images or videos.

In a study (R. U. Khan, K. Khan,2021)]the author’s study looks at how AI is possible to use machine learning to diagnose plant diseases in agriculture and can be identified using this method. Therefore, the need for food is on the rise as the world's population rises, and the frequency and accuracy with which plant and animal illnesses may be diagnosed has increased thanks to advances in technology. Still, early diagnosis may be challenging for certain illnesses, making pandemics a real possibility. The study's primary objective is to determine the characteristics of each illness and how best to use AI for rapid diagnosis. This study analyses different plant disease datasets with a focus on the deep learning methodology that has emerged as the dominant machine learning strategy over the last five years. The study also deals with problems and challenges encountered by the present methods used to identify plant diseases. The goal is to create a rapid and accurate approach for diagnosing plant illnesses that will aid in the fight against global epidemics and guarantee the safety of our food supply.

Table 1
Several bacterial, fungi, and virus-related plant diseases

Bacterial Disease	Fungal Disease	Viral Disease
Ring Rot, Brown Rot	Ergot, Green Ear	Red Leaf
Blight	Tikka	Bunchy Tap
Canker	Blast	Leaf Curl
Black Aram	Downy	Mosaic

In a study (M. E. H. Chowdhury *et al,2021*) the author’s study, using a newly constructed convolutional neural network called Efficient Net, based on an examination of 18,161 images of tomato leaves, we suggest Using deep learning to identify afflicted tomato plants (whole and cut up into smaller pieces). Improvements to the U-Net segmentation models used in this application, the study assesses the precision, IoU, and Dice scores of these two segmentation models. In addition to binary classification (healthy leaves and unhealthy leaves), the research also compares the effectiveness of these models to six-class classifications (healthy leaves and a variety of an enhanced U-net segmentation system achieves 98.66% accuracy, 98.5% IoU, and 98.73% dice score for the classification of unhealthy leaves. Binary classification accuracy reaches 99.95% and six-class classification accuracy reaches 99.12%. using segmented images, EfficientNet-B7 outperformed the competition. For segmented images, the classification accuracy of Efficient, Net-ten-class

B4 was 99.89%. In conclusion, the research found that by using segmented images to train deeper networks, all designs outperformed earlier published literature in their ability to identify diseases.

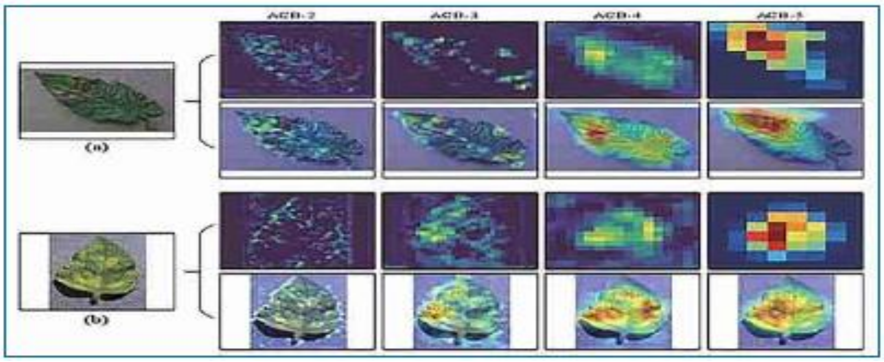

Figure 2: A visual representation of plant disease results:(L. Li, S. Zhang, and B. Wang,2021)

In a recent research (S. Luo, J. Yu, Y. Xi,2022), a novel approach is proposed to remotely sense airplanes to increase the accuracy with which aircraft targets are identified against complex backdrops. The YOLOv5 network was expanded to enhance its image-processing capabilities. Here are three improvements we added to the YOLOv5-Aircraft model: Adding scaling and centering calibrations to the main batch normalization module enhances the relevant features and produces a more consistent distribution of features. In general, smoothed Kullback-Leibler divergence performs better than the cross-entropy loss function. iii) To reduce data loss, low-resolution feature layers are deleted to prevent semantic loss in the CSandGlass module, which replaces the residual module. Experimental findings demonstrate that the YOLOv5-Aircraft model may facilitate simpler convergence while increasing the speed with which aircraft target detection is performed.

In a study (M. Arsenovic, M. Karanovic,2019) the author highlights the shortcomings of conventional methods for identifying plant diseases and introduces An innovative deep-learning algorithm that was used to collect 79,265 pictures of leaves. The collection was expanded using generative adversarial networks and traditional augmentation techniques. The effectiveness of training and application in a controlled context was evaluated, and real-world plant disease identification tasks, such as detecting many illnesses on one leaf, were evaluated. Using a two-stage neural network architecture, this study recommends a method for determining plant illness severity. The trained model was 93.67%

accurate; this study aims to create a strong instrument with exceptionally precise results for plant disease categorization in agriculture.

A study (M. Arsenovic, M. Karanovic,2017) investigated the effectiveness of real-time analysis of images acquired by cameras with different pixel counts for identifying diseases and pests. VGG nets and ResNet are among the deep feature extractors examined in the study, Faster Region-based Convolutional Neural Networks, the Single Shot Multibox Detector, and the Region-based Fully Convolutional Network are different methods. To improve precision and reduce false positives, the researchers recommend local and global class annotations. Several inter- and extra-class variables such as infection stage and plant location are included in the Tomato Diseases and Pests Dataset for training and testing the system. According to the trials, the system can adapt to a wide variety of challenging environments and is sensitive to nine distinct plant diseases and pests.

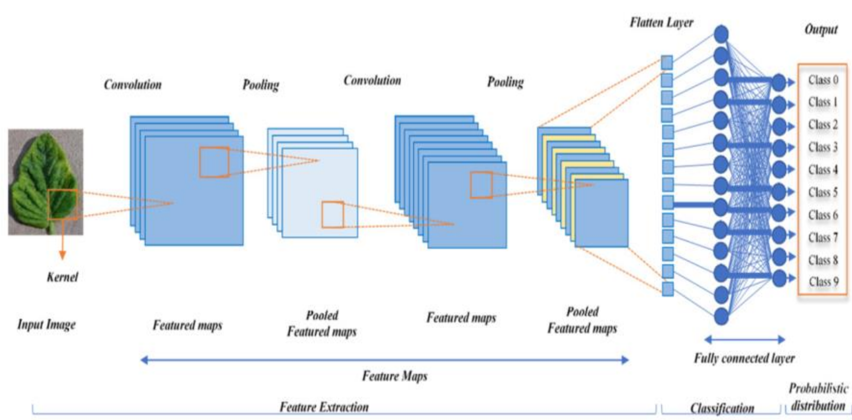

Figure 3: Block Diagram of Plant Disease Detection Method

In a study, the author (M. Shoaib *et al,2022*), examines 18,161 images of tomato leaves (both unsegmented and segmented) using a newly created accuracy, IoU, and Dice scores are compared and contrasted between EfficientNet and U-net, a convolutional neural network developed for identifying blight in tomatoes. Further, leaf health is classified as either good or poor., the research also compares the effectiveness of these models to six-class classifications (healthy leaves and a variety of sick leaves) and ten-class classifications (healthy leaves and a variety of unhealthy leaves. A better segmentation accuracy of 98.6%, a higher IOU accuracy of 98.5%, and a higher Dice score of 98.73% were achieved using U-net segmentation. An accuracy of 99.96%

for binary and 99.12% for six-class classification was achieved with segmented images. Compared to its competitors, EfficientNet-B7 performed significantly better. EfficientNet-ten-class B4 achieved 99.89% classification accuracy on segmented images. As a result, all designs performed better than earlier published literature in detecting diseases using deep networks trained on segmented images.

In a study (A. Artificial, D. Li Liu,2022) the author explained wrapper technique for disease classification in plant leaves is constructed using Comparing and contrasting flower pollination algorithms (FPAs) with SVMs and CNNs (CNNs This method uses metaheuristic optimization strategies to choose characteristics that are both accurate and easy on the CPU. Features were extracted with the 2D-DWT, and apple, grape, and tomato plant photos were collected. Excellent classifier performance was preserved with the employment of SVM and FPA algorithms used to select features. The particle swarm optimization (PSO) method was used as a comparison point for the suggested optimization technique. To simplify Enhancing the classification model and speed up the process in real-time, a CNN classifier based on one classification layer was utilized. Using an unmanned aerial vehicle and the NVIDIA Jetson Nano development kit, the final model was tested on tomato, apple, and grape plants (UAV). The results of the trials validated the model's capability of making rapid, accurate diagnoses of leaf diseases on plants in the wild. The proposed model is a highly efficient hybrid classifier that makes use of a minimum number of features without sacrificing accuracy in the classification process.

In another study, the author (J. G. Arnal Barbedo,2019), identifies plant diseases, this research explores how deep learning may be used for the categorization of images. The absence of diverse enough picture datasets to depict the large variety of illnesses and symptoms seen in reality is the fundamental obstacle confronting this technique. Rather than collecting data on full leaves, as is commonly done, the authors of this research propose collecting data on individual lesions and spots to improve data variability and better detect several illnesses on a single leaf. However, complete automation is not possible due to the need for human symptom categorization in this method. In comparison to utilizing the original photos, this method improved accuracy by an average of 12%, and no crop achieved an accuracy of less than 75%, even while taking into account a total of 10 different illnesses. These results imply that given enough data, deep learning algorithms might be beneficial for identifying and diagnosing plant illnesses.

A study (A. Fuentes, S. Yoon,2020) suggests that deep learning can be used to diagnose plant illnesses and is effective in this study. This research intends to provide farmers access to a tool that will improve crop management by addressing the problem of poor performance in real-world settings this study, two deep learning approaches are proposed to identify plant diseases. The first approach uses plant disease detection and localization are accomplished with Meta-architectures and feature extractors help. In the second approach, a refining function called Filter Bank is used to correct for class imbalance and false positives. Researchers gathered and documented data on illnesses and pests that affect tomato plants to verify the strategies' efficacy. The study's findings confirm that plant diseases may be identified with high accuracy even in realistic, high-variance settings. It sheds light on the potential and limitations of deep learning when it comes to identifying plant diseases.

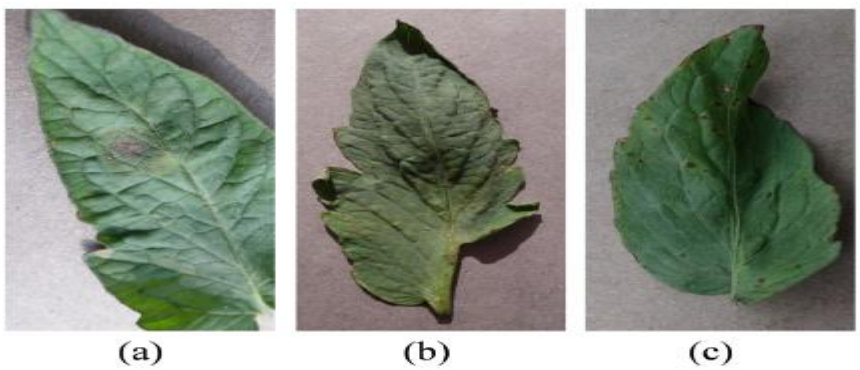

Figure 4: Three Types of Tomato Plant Disease a) Late Blight b) Target c) Bacterial Spot (J. Lu, R. Ehsani, Y. Shi,2018)

Deep learning models are explored in a study (B. P. Zen, I. K. A,2022). A deep learning model is being to develop AI that can diagnose plant diseases. The plant diseases are identified by the program via the use of camera-object matching. In this research, plant illnesses are identified Using convolution neural networks and recurrent neural networks. The results of the disease prediction tests on the tomato plant samples were one hundred percent for Early Blight, ninety percent for Bacterial Spots, one hundred percent for Healthy, and one hundred percent for Late Blight. With the system's ability to provide medical care suggestions for crops based on photographs, farmers will have an easier time determining the nature of various plant ailments. This program was developed to aid farmers in lowering the rate of crop failure due to plant diseases and raising the standard of agricultural and plantation output.

It is explained that leaf diseases are a major cause of yield loss and quality decline in many crops, making their detection and categorization an absolute need in crop production (M. Jaithoon Bibi, S. Karpagavalli,2021). Crop diseases, which may be caused by a wide variety of microbes and pathogens, are known to stunt crop development and even lead to total crop failure, according to the available research. Deep learning and other sophisticated algorithms are needed for accurate crop leaf disease diagnosis and A comprehensive review is provided here of the current state of the art in using deep learning algorithms to identify and classify crop leaf diseases. Toward the end of the article, a comprehensive analysis is provided, along with suggestions for improving leaf disease identification accuracy.

The threats to food security are investigated, which looks at how big data and using deep learning to diagnose and predict plant diseases is one potential application (A. H. Basori, A. B. F. Mansur,2020). Features including leaves, weather, soil, and other landscape characteristics are the primary inputs of interest in this research. To gather data and pinpoint diseased plants, the suggested framework, dubbed Smart Farming, makes use Utilizing IoT technology as well as GPS tracking and computer vision. The research found that deep learning outperformed logistic regression in detecting diseased leaves, with an accuracy of 72%. If the framework can identify and locate plant illnesses quickly enough, it might be a game-changer in the fight against their proliferation. This has the potential to be especially useful for farms with a substantial amount of land. A potential direction for future research is to use data captured in real time by drones or CCTV cameras installed on working farms.

A study (J. Li, Y. Qiao, S. Liu,2022) suggests using YOLOv5s to create a better algorithm for identifying diseases in vegetables. The authors hope to remedy the problem of illness detection in vegetables, which is complicated by the fact that many diseases look the same and are prone to interference from environmental variables. The algorithm's primary goal is to boost YOLOv5s by enhancing the CSP, FPN, and NMS modules in such a way that external influences are reduced, multi-scale feature extraction is improved, and detection range and performance are both elevated. 1000 labeled photos of five illnesses were used to evaluate the algorithm, yielding a 93.1% mAP for vegetable disease identification and a decrease in missing and erroneous detection due to complicated backdrops, leading to an increase in A detection time of 0.03 seconds and a model size of 17.1 MB are used to examine the impact of spotting and pinpointing a disease on localized outbreaks. the method provides a novel theoretical foundation and research ideas for illness identification, as well as improved detection and localization accuracy compared to competing techniques.

In a study(J. Chen, J. Chen, D. Zhang,2020) the author explained Food security and agricultural output may benefit from A machine learning system that identifies and diagnoses diseases in plants by using deep learning techniques, such as using pre-trained models from big datasets, which has proven useful for this purpose. The authors of this study used transfer learning with Inception and VGGNet modules have been pre-trained on ImageNet, and discovered that their approach achieved validation of A public dataset with 91.83 percent precision and images of rice plants with 92 percent precision, despite the presence of complex background conditions. The identification of plant diseases with this method is quick and accurate.

In a study(Y. Guo *et al,2020*) the author explained, using deep learning, the authors of this work present a mathematical model for disease identification and detection in plants. By segmenting leaf images using the Chan-Vese method, disease signs can be detected, and then affected areas can be identified and located using an area proposal network. Our model was tested against three different diseases, based on a basic background, after training on damaged leaves. With an accuracy of 83.57 percent, the model outperforms conventional techniques and has the potential to boost crop yields and advance agricultural sustainability.

In an article (W. S. Kim, D. H. Lee,2020), they provided an image-based system for the automated surveillance of agricultural fields. An onion field monitoring system, a deep neural network model to identify illness signs, and a performance assessment are the core components of the system. Monitoring systems in the field consist of pan-tilt-zoom cameras, motors, wireless transmitters, and picture recording modules. Deep learning models are trained via weakly supervised learning and then utilized.to identify and locate objects based on annotations at the picture level. The model is capable of classifying 6 distinct illness signs based on training data from field monitoring system photos of onions. Based on a peak activation map cutoff of 60% is ideal for isolating the illness symptom from the background. The system's performance was measured using the mAP metric with an IoU of 0.5, and the findings demonstrate that it can identify signs of onion disease in real-time with a mAP range of 74.1 to 87.2%. The use of simple images of healthy and diseased leaves has recently been demonstrated to allow deep learning to be used in the diagnosis and identification of plant illnesses(K. P. Ferentinos,2018). Using convolutional neural networks (CNNs) for training. The models were trained using 87,848 photos from a publicly available database that depicts 25 plant species and 58 disease and non-disease groups, as well as healthy plants. Many models were trained, but the best one correctly identified the correct plant disease or healthy plant 99.53% of the time. Given its excellent predictive accuracy, the model might be developed for use in actual production settings to back up an integrated plant disease diagnosis system.

Table 2
Comparison of Various Models with Accuracy

Detection Model	Accuracy
Multi-Class Plant Disease Detection Model Based	**95%**
Optimized YOLOv5	**92%**
Improved YOLOV5	**86.8%**
The mobile-based deep learning model	**83.2%**
EfficientNet CNN model Two-class classification	**99.5%**
PlantDiseaseNet Model	**93.67%**

In a study (Y. Li, J. Nie, and X. Chao,2020) the author examined whether deep learning and more specifically deep CNNs could be used to detect plant diseases early. The concern that emerges, however, is whether or not shallow CNNs can glean sufficient information for this purpose. A few approaches have been presented to deal with this issue, including Three datasets using SCNN-KSVM, SCNN-RF, and Random Forests. An in-depth comparison of SCNN-KSVM and SCNN-RF with other deep-learning models revealed significant differences while having fewer parameters. An efficient and straightforward method of identifying plant diseases involves combining shallow CNNs with traditional machine-learning methods.

Conclusion

Our findings demonstrate that deep learning algorithms can be used to identify plant diseases. These results demonstrate the potential of deep learning as a means of classifying diseases. Generally, deep learning-based plant disease detection systems have the potential to completely change how we handle plant diseases and contribute to the security of our population's food supply. To address the remaining issues and achieve the full potential of this technology, more research and development in this field are required.

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